Correcting Multiple Forms of Bias in the Wage Equation of Women Using Conditional Mixed Processes

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Abstract

Additional education is expected to increase wages. This is supported by a wide literature in labor economics. However, measuring education's effect on wages is complicated by various sources of bias. Two common sources of contamination are ability bias (self-selection into education) and self-selection into employment. A common method to control for ability bias is with Instrumental Variables (IV) regression, while a common method to control for employment selection is Heckman correction. Using NLSY97 longitudinal survey data, I employ a conditional mixed process (CMP) method to jointly apply IV and Heckman corrections to a model of adult female wages. This appears to be the first application of CMP to combining these corrections. I find that IV alone increases the measured education effect (versus OLS), while Heckman correction decreases it. Controlling for both sources of bias, the education effect is estimated to be about 10%, which is slightly larger than an OLS model, and is consistent with existing literature. The CMP method shows promise for simultaneously correcting biases common to the wage equation.

*A complete replication package for this paper (including code) is available at https://github.com/svanomm/labor-economics-final.

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I. Introduction

People with more education tend to make more money. Education is the primary determinant of human capital, the set of abilities and acquired skills workers offer to the labor market.[1] One method to estimate the effect of increased education on wages is to simply compare the average hourly wages of people at various levels of education. For example, we might compare wages of people with only a high school degree to people who completed one year of college. The assumption would be that the difference in wages is the effect of pursuing 1 additional year of education.

However, all people have an innate ability/work ethic, and this ability level differs from person to person. Some people end up being more productive than others by chance, and that productivity translates to increased wages regardless of their education. The issue is that people with more innate ability are more likely to pursue additional education, creating an **ability bias**. One reason for this is that people with more ability are likely to get more value out of education: a greater capacity to understand their classes will transfer to more skills gained in school. People self-select into more education based on their ability level, and both ability level and education determine their wages.

Empirical studies often control for ability bias with **Instrumental Variables (IV) regression** (also called two-stage least squares or 2SLS). IV regression involves identifying "instruments" that are correlated with the endogenous variable (education) but uncorrelated with the residuals of the wage equation. The IV procedure uses the instruments to predict educational attainment without the ability bias, then uses the predictions as a control in the wage model.[2] This process reduces or eliminates the endogeneity of education in the wage equation, i.e. the ability bias.

We can only estimate a wage equation for people who have a wage, i.e. who choose to work. But selection into employment is not random: people who choose to work are likely

[1]Borjas (2023), p. 213.

[2]I have described the two-stage version of the procedure, but other techniques estimate both equations simultaneously.

systematically different from people who choose not to work, introducing a sample selection bias to our results. This selection is often studied for women, who historically are more likely to exit the job market to take care of their children. Women with less earnings potential, ability, and/or education are more likely to exit the job market, all else equal.

Studies often control for selection into employment with a Heckman (1979) correction procedure. The idea is to first model the decision to work based on observed data, and then incorporate a bias correction term into the wage equation based on the probability of employment.[3] This additional term reduces or eliminates the endogeneity of the decision to work, i.e. the employment selection.

While both methods are commonly employed to reduce bias in the wage equation, they are rarely combined in a joint specification. Conceptually, applying both bias correction techniques seems attractive. After all, employment selection bias does not disappear when controlling for ability bias, and vice versa. Practically speaking, however, combining these approaches is more complicated and computationally difficult. Fortunately, as discussed below, conditional mixed process (CMP) analysis allows for a straightforward application of such corrections.

II. Literature Review

A. Education Effect for Women

Existing literature generally finds that the return to education for women is typically higher than for men.[4] Additionally, Card (1999) explains that IV studies of the return to education generally result in larger estimated effects, though the effect is less clear when applied specifically to women. Selected estimates from the literature are shown below.

[3] I have described the two-stage version of the procedure, but maximum likelihood techniques can estimate both equations simultaneously.

[4] For example, see Dougherty (2005).

Table 1: Selected Returns to Women's Education

Author	Estimate
Card (1999) (OLS)	0.112
Card (1999) (IV)	0.110
Hannum et al. (2013) (China)	0.113
Montenegro and Patrinos (2023) (North America)	13.8%
Montenegro and Patrinos (2023) (World)	11.6%
Psacharopoulos and Patrinos (2018) (World)	≈ 10%
Tembon and Fort (2008) (World)	9.8%

Coefficients are from models of log wages unless denoted with a % symbol.

Various reasons why the female return should be larger than the male return have been proposed. Dougherty (2005) explains that, in addition to increasing their human capital, education for women indirectly reduces the effects of gender discrimination in the labor market. Hannum et al. (2013) show that there is a selection bias at play: less educated women are more likely to be married and trade their spouse's income for their own. The authors find that after controlling for this bias, there is no difference in returns by sex (in China).

B. Conditional Mixed Process (CMP)

The CMP method was first described in Roodman (2011), who created a Stata package of the same name.[5] CMP is best described as a generalized version of the Zellner (1962) seemingly unrelated regression (SUR) method, which estimates systems of equations with potentially correlated error terms.[6]

CMP generalizes SUR in a few important ways, as described by Baum (2016). First, CMP allows for a mix of non-linear equations with limited dependent variables. Second,

[5]There does not appear to be a CMP package for any other statistical software.

[6]While initially designed to fit recursive systems of equations with fully-observed endogenous variables, Roodman has greatly expanded the estimator to allow for more general systems of equations with more general interactions. These expansions are documented only in Baum (2016) and the documentation for the cmp package.

equations can be run on different subsets of the available data. And third, CMP can estimate general systems of equations simultaneously via maximum likelihood estimation, resulting in potential efficiency gains. The first two points allow for the combination of IV and Heckman correction in this paper. There is a small existing literature on the application of CMP to labor economics issues.[7]

Tracey et al. (2024) use CMP to study how parental limits on child technology usage impact academic success. Parents decide how much effort to devote to monitoring their children's use of technology, and children decide how much effort to devote to their academic studies. The authors estimate a system of two ordered probit models with correlated errors using CMP, finding that stricter technology limits increase GPA in some subjects, but not in others.

Kalenkoski and Pabilonia (2012) study the effects of student employment on health and academic outcomes using CMP. The authors estimate a system of four correlated equations on employment status and homework, screen, and sleep time. The first equation is probit, the next two are Tobit, and the sleep equation is linear. The model finds that student employment decreases sleep and homework time while simultaneously reducing screen time. This article demonstrates the powerful ability of CMP to combine diverse equations with correlated error terms.

Elmallakh and Wahba (2022) study what happens to wages when Egyptians temporarily migrate (legally or not) to another country, then return to their home country for work. CMP is used to account for selection into migration, selection into legal status, and selection into return. The authors show that home wages do not increase after a period of illegal migration, while migrating legally comes with a wage premium upon return.

[7]There does not appear to be any existing use of CMP to correct ability/employment selection biases in the wage equation, nor has CMP been applied to NLSY97 data in the literature.

III. Data

For my analysis, I use the Bureau of Labor Statistics' National Longitudinal Survey of Youth 1997 (NLSY97).[8] The BLS describes the data as:[9]

> a nationally representative sample of 8,984 men and women born during the years 1980 through 1984 and living in the United States at the time of the initial survey in 1997. Participants were ages 12 to 16 as of December 31, 1996. Interviews were conducted annually from 1997 to 2011 and biennially since then. The ongoing cohort has been surveyed 21 times as of date. Data are available from Round 1 (1997–98) through Round 20 (2021–22).

I collected various demographic information from the survey data, as well as education of the respondent's biological parents. Variables that could change over time (such as wage and years of education) were collected for 2010, 2011, 2013, 2015, 2017, 2019, and 2021, giving up to 7 years of panel data on wage and education per person (subject to panel attrition). The data were also limited to females only.

The work experience variable I use is based on total number of hours worked in each year, rather than months or weeks. The idea is to treat someone who works 60 hours per week as "more experienced" than one who works 30 hours per week.[10] After adding the reported hours worked in each year, I divide by 2000 to get cumulative work experience in Full Time Equivalent (FTE) years.[11] Additionally, I only consider work experience from 2002 onward, where the youngest respondents were at least 18 years old.

Certain questions on the respondent's use of drugs and attitude towards school were collected at the beginning of the survey (in 1997 or 1998). I use these questions to create scores reflecting the respondent's preferences for risk and education. I use the drug questions to create a "Drug Intensity" score, where a higher value indicates a more extensive use of

[8] https://nlsinfo.org/investigator/pages/home.

[9] https://www.bls.gov/nls/nlsy97.htm.

[10] Since most marketable skills are learned by experience, this is not an unrealistic approach. Hours are capped at 4000 per year (roughly 80 hours per week) to remove the influence of outliers or mistaken data entries.

[11] https://www.wallstreetprep.com/knowledge/fte-full-time-equivalent/.

drugs during childhood.[12] I use the school questions to create a "School Quality" score, where a higher value indicates that the student is more likely to enjoy school.[13]

A summary of my collected variables is below. The regression dataset has 18,498 observations on 3,079 women.

Table 2: Summary Statistics

Statistic	Min	25%	Mean	Median	75%	Max
Wage ($/hr)	5	12.5	23.1	17.8	26.4	241.7
Work Experience	0	5.9	9.7	9.2	13.3	34.4
Years of Education	6	12	14.5	14	16	20
Age	26	30	33.0	33	36	41
Dad's Education	2	12	12.6	12	14	20
Mom's Education	1	12	12.6	12	14	20
% Working			83.7			
% Black			24.7			
% Hispanic			19.7			
% Married			46.1			
% Parents Divorced			7.7			
Drug Intensity	0	0	4.8	0	1	90
School Quality	-7	0	1.2	2	3	5.0
Number of Children	0	0	0.9	0	2	8.0

IV. Methodology

Below, I describe the econometric specifications tested with the regression data. All specifications use standard errors clustered by survey participant to account for within-subject autocorrelation.

[12] The score is created by adding the number of days the respondent used each type of drug (in the past 30 days), with equal weight. One question on cocaine use is a Yes/No, for which I assign a value of 15 to a Yes. The lowest possible score is 0 and highest possible score is 105.

[13] The score is created by adding 1 for answering Yes to a positive-sentiment question and subtracting 1 for answering Yes to a negative-sentiment question. The lowest possible score is -7 and highest possible score is 5.

A. OLS

Two main OLS models were tested. First, a simple Mincer (1958) equation regresses log of wages on years of education, work experience, and work experience squared. Since there are multiple years of data per person, these variables change from year to year.[14] Next, I add control variables for Black, Hispanic, number of children, and fixed effects by Census region. The latter two variables are allowed to change over time.

B. Instrumental Variables (IV)

The instruments used in my analysis are: Father's Education, Mother's Education, Parents Divorced, Drug Intensity Score, and School Quality Score.

The use of parents' education as an instrument is well known in the literature.[15] It is fairly obvious that parents have a significant influence on their child's educational attainment: parents with more education generally encourage their children to get more education as well. Parental education likely has little direct effect on their child's eventual wage, making it a suitable instrument for IV.[16]

My additional instruments are motivated by the idea that personal hardship and attitude to education during childhood should influence educational attainment while not correlating with residuals from the wage equation. Children whose parents were divorced may associate school with that negative experience, pushing them away from education. Children who used drugs have preferences for riskier and more immediate benefits, rejecting education. Finally, children with more positive attitudes toward school should pursue more schooling. While there is no way to empirically verify the IV exclusion restriction, i.e. that the instrument is uncorrelated with the wage equation residuals, the child's drug use and attitude toward

[14] While I analyze the 2010-2021 period, where subjects were at least 26 years old, approximately 1 out of 4 subjects obtained additional education during the analysis period.

[15] See Card (1999).

[16] Some well-educated parents might help their children find better jobs, though this seems unlikely to occur systematically. Well-educated parents might also pass on better genes to their children or parent their children better.

school are far removed in time from their eventual wages.

I test two IV models. The first model only uses parents' education as instruments, while the second IV model includes the drug and school instruments as well. The wage equation is the same as the OLS model with controls specified above, though including the IV-corrected education term.

C. Heckman Correction

While the OLS and IV models above are restricted to wage earners only, the Heckman model incorporates non-wage-earners to account for selection bias.

The selection equation regresses a flag for working status on Black, Hispanic, number of children, age, and marital status. The number of children and marital status variables are expected to affect women's work status: women with more children are less likely to work, and some married women are also less likely to work as they rely on their spouse's income.

The wage equation is the same as the OLS model with controls specified above, though including the correction term created by the first equation. Both equations are estimated using Stata's `heckman` command, which uses a Maximum Likelihood Estimation approach rather than a two-stage OLS approach.[17] Importantly, the model assumes that the errors for each equation are jointly Normal, which is typically more of an issue in small samples. The data here are large enough, and the log wage distribution is necessarily "nice" enough from data processing, that this assumption is appropriate for our purposes.

D. Heckman + IV with CMP

CMP analysis is used to combine the endogenous education correction from IV with the selection probability correction from the Heckit model.[18] This is made straightforward with the Stata package `cmp`, created by Roodman (2011).

[17]The two-stage approach yields a practically identical result.
[18]I use the terms "Heckit" and "Heckman correction" interchangeably here and below.

The model estimates a system of three equations: the wage equation as specified above, the education model from the IV first stage, and the selection equation on working status from the Heckit model. The only other input to the `cmp` function is an indication of the type of each equation. One additional note is that in the CMP model, the education equation is estimated on *all* participants, not just wage earners. This seems more realistic in principle, because we should not expect the education equation to be the same for workers and non-workers.

An alternative approach for jointly correcting endogenous ability and employment selection is described by Wooldridge (2010). His proposal is to first obtain the Inverse Mills Ratio from the selection equation, and then to use the IMR along with other instruments in estimating the 2SLS wage equation on wage earners.[19] However, the resulting standard errors need to be adjusted to account for the multiple equations. CMP estimates the entire system in one step, calculates appropriate clustered standard errors, and allows for the residuals between the equations to be correlated. CMP is also easily extended to include additional bias correction techniques, while the alternative would become much more complicated.

E. Sensitivities

Finally, I report some sensitivity models to ensure the robustness of my results. For the OLS model, I include fixed effects by participant as a sensitivity. For the IV model, I use Stata's `xtivreg` command to incorporate Random Effects (RE) into both of the main models. For the Heckman model, I also include RE by participant.[20] For the CMP model, I include RE by participant. I also test a CMP model in which endogenous education is allowed in the selection equation.[21]

[19] Applying this method to my data gives an estimated return that is approximately equal to the CMP estimate.

[20] This is accomplished through the `cmp` command rather than Stata's `xtheckman`, which took far longer to compute.

[21] In other words, the predicted education from the IV education regression is included in the selection equation.

V. Results

A. OLS

The results of my two OLS models are shown below. The models provide very similar returns to education, with the standard Mincer equation estimating an effect of 8.8% and the additional controls estimating a slightly lower effect of 8.4%.[22] I find no diminishing returns to work experience (the squared term is not statistically significant), but this is likely due to my participants being within a limited age range of 26 to 41. I also find that wages are lower for women with children, and the effect increases with the number of children in the household.[23]

Table 3: OLS Regression Results

	OLS 1	OLS 2
Years of Education	0.084***	0.081***
Work Experience	0.031***	0.029***
Work Experience Squared	0.000	0.000
Black		-0.137***
Hispanic		-0.014
Number of Children		-0.017***
Constant	1.352***	1.540***
Observations	15,490	15,352
Adjusted R-squared	0.309	0.335
Region FE	No	Yes

Standard errors clustered by participant. *** p<0.01, ** p<0.05, * p<0.1.

B. Instrumental Variables

I report both stages of my IV regressions below.[24] The first stage results show that both parents' education contributes to their daughter's educational attainment, with Mom's edu-

[22]Through the rest of this paper, I use the equation $\exp(x) - 1$ to translate reported coefficients into a percent effect.

[23]This is consistent with the so-called "motherhood penalty," in which women tend to have reduced wages after having children. See Correll et al. (2007) for an example.

[24]The parental divorce variable was found to not be a significant predictor of education, and so was excluded here.

cation having a slightly higher impact. My additional instruments have the expected signs: higher drug use in childhood translates to less educational attainment, while a more positive outlook on school in childhood translates to more education. Comparing IV 1 to IV 2 shows that my instruments improve the model fit, with adjusted R-Squared increasing from 0.158 to 0.205.

The second stages of my IV regressions estimate noticeably higher returns to education compared to the OLS results: 14.0% and 12.5% for IV 1 and IV 2, respectively. Interestingly, the IV models both show curvature with respect to work experience, and the number of children no longer has a statistically significant impact on wages.

Table 4: IV Regression Results

Stage 1

	IV 1 Education	IV 2 Education
Dad's Education	0.202***	0.188***
Mom's Education	0.223***	0.221***
Childhood Drug Use Score		-0.032***
School Quality Score		0.201***
Constant	9.337***	9.414***
Observations	15,490	15,490
Adjusted R-squared	0.158	0.205
Region FE	No	No

Stage 2

	IV 1 Log(Wage)	IV 2 Log(Wage)
Years of Education	0.131***	0.118***
Work Experience	0.016***	0.019***
Work Experience Squared	0.001***	0.001**
Black	-0.117***	-0.122***
Hispanic	0.042**	0.028
Number of Children	0.006	0.000
Constant	0.848***	1.021***
Observations	15,352	15,352
Adjusted R-squared	0.280	0.304
Region FE	Yes	Yes

Standard errors clustered by participant. *** p<0.01, ** p<0.05, * p<0.1.

C. Heckman Correction

I now report both stages of my Heckman model. The first stage selection equation shows that all instruments used have a negative effect on the probability of working. Compared to all other races, Black and Hispanic women in this sample are generally less likely to work. Probability of working declines substantially with the number of children, such that a woman with 3 children is 36% less likely to work than a woman without children.[25] Older women in the data are less likely to work, though the result should take into consideration the limited

[25] $\exp(3 * -0.151) - 1 = -36.4\%$.

age range in the data. Finally, the model confirms that married women are less likely to work than single women. I would caution against interpreting any one of these coefficients on its own, as they are likely correlated. For example, older women are more likely to be married as well as have more children.

The second stage of the Heckit model shows that after correcting for selection bias, the return to education is much smaller than for an OLS model, at 7.4%. This change, combined with the high value of ρ, demonstrates that selection into employment is an important source of bias to account for in the female wage equation.

Table 5: Heckman Selection Results

Stage 1 (Probit)

	Work Status
Black	-0.142***
Hispanic	-0.127***
Number of Children	-0.151***
Age	-0.012***
Married	-0.095***
Constant	1.594***
Observations	18,360
Region FE	No
ρ	0.917

Stage 2

	Log(Wage)
Years of Education	0.071***
Work Experience	0.031***
Work Experience Squared	0.000
Black	-0.133***
Hispanic	-0.020
Number of Children	-0.056***
Constant	1.579***
Observations	18,360
Region FE	Yes
ρ	0.917

Standard errors clustered by participant. *** p<0.01, ** p<0.05, * p<0.1.

D. CMP and Summary

I now report the models above, along with the final CMP model which combines the IV 2 and Heckit models. The CMP model finds a return to education of 10.2%, which is very nearly equal to a simple average of the IV 2 and Heckit estimates. While not reported in the table, the `cmp` command found statistically significant correlations between the equations, motivating the need for both the IV and Heckit corrections.

Viewing all models together shows that the estimated control coefficients are stable for the most part, although the effect of number of children disappears in the IV models. The estimated returns to education range from 7 to 14%, with the Heckit correction alone representing the minimum and the IV correction alone representing the maximum estimate. Both OLS and the CMP models fall in the middle.

Table 6: Regression Results

	OLS 1	OLS 2	IV 1	IV 2	Heckit	IV+Heckit
Years of Education	0.084***	0.081***	0.131***	0.118***	0.071***	0.097***
	(0.003)	(0.003)	(0.008)	(0.007)	(0.003)	(0.006)
Work Experience	0.031***	0.029***	0.016***	0.019***	0.031***	0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Work Experience Squared	0.000	0.000	0.001***	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black		-0.137***	-0.117***	-0.122***	-0.133***	-0.121***
		(0.018)	(0.019)	(0.019)	(0.020)	(0.020)
Hispanic		-0.014	0.042**	0.028	-0.020	0.009
		(0.019)	(0.021)	(0.020)	(0.021)	(0.022)
Number of Children		-0.017***	0.006	0.000	-0.056***	-0.046***
		(0.023)	(0.024)	(0.024)	(0.022)	(0.021)
Constant	1.352***	1.540***	0.848***	1.021***	1.579***	1.200***
	(0.042)	(0.048)	(0.115)	(0.097)	(0.047)	(0.093)
Observations	15,490	15,352	15,352	15,352	18,360	18,498
Adjusted R-squared	0.309	0.335	0.280	0.304		
Region FE	No	Yes	Yes	Yes	Yes	Yes

Standard errors clustered by participant. *** p<0.01, ** p<0.05, * p<0.1.

E. Sensitivities

Sensitivity regression results are summarized below. All measured effects continue to be positive and statistically significant. Adding fixed effects to the OLS model dramatically reduces the estimated return to education to just 3.6%. This is partially due to the fixed effects removing the indirect effects of increased education on wages, which Dougherty (2005) explains is an important contribution to the overall effect.

One other noteworthy finding is the "IV+Heckit Endogenous" model, which allows education to enter the employment selection equation. This CMP model simultaneously applies the IV correction to both wages *and* the employment decision, and estimates a return to education that is higher than the IV 2 model alone. Code output for the selection equation shows a coefficient on ability-corrected education of 0.158, with $p < 0.000$. More educated women are much more likely to work, which is not a surprising result.

Table 7: Summary of Sensitivities

Model	Coefficient	SE
OLS w/ FE	0.035***	(0.008)
IV 1 RE	0.117***	(0.007)
IV 2 RE	0.108***	(0.006)
Heckit RE	0.067***	(0.003)
IV+Heckit Endogenous	0.129***	(0.007)
IV+Heckit RE	0.104***	(0.006)

Standard errors clustered by participant. *** p<0.01, ** p<0.05, * p<0.1.

VI. Discussion

My main CMP model finds a return to education for adult women of around 10%. This is on the lower end of existing results in the literature as shown in Table 1. Unfortunately, there is little to no existing literature that incorporates IV and Heckman correction into the estimates for a direct comparison to the CMP model. The closest comparison available comes from Wooldridge (2010), who finds a coefficient of 0.088 for married women after accounting for sample selection and ability bias.[26] The result that Heckman correction generally decreases the return may explain why my estimate is lower than the existing literature discussed above (which come from IV or OLS estimates).

Interpretation of my results should consider the limited scope of my data. I analyzed U.S. adult women aged 26 to 41. The NLSY97 includes an oversample of Black and Hispanic respondents, meaning it is not representative of the U.S. population.[27] I additionally measure a single, homogenous return to education. In reality, the return will differ by a variety of observables. For example, the return may change depending on what type of education

[26]Since married women are more likely to be unemployed than women in general, it makes sense that Wooldridge (2010) found a lower coefficient than my CMP model.

[27]I did not correct for overrepresentation in the sample.

(primary, secondary, tertiary) is added, and when.[28] It will also differ depending on the area of education and eventual area of work. Future work should measure the heterogeneity of returns on available data, with and without various bias corrections.

A. Policy Applications

Measuring an accurate return to education is important for people to understand the benefit of education, and for government agencies to set appropriate policy. Adult workers and parents alike want to calibrate their expectations of future income to the most accurate information possible, and so an underestimated return could cause parents to not push their child toward further education as much as they would have otherwise. An overestimated return could be just as damaging. In particular, the IV models provide overly optimistic returns to education, because they fail to account for the selection problem that not all women who pursue higher education will end up working. As a result, federal student loan programs must consider accurate return estimates to ensure that the programs are not under- or over-funded. The over $1 trillion in outstanding U.S. student loan debt could be a consequence of overly-optimistic forecasts of the return to education.[29]

B. Extensions

As explained above, the CMP method easily incorporates additional bias corrections. One could imagine including many more equations to account for selection into marriage, interactions with spouse's income/employment, selection into specific industries based on parents' jobs, and endogenous survey attrition. Further work should explore how such corrections interact with the more common bias correction techniques discussed in this paper.

[28] See Montenegro and Patrinos (2023).
[29] https://www.pgpf.org/article/10-key-facts-about-student-debt-in-the-united-states/.

VII. Conclusion

I estimated the return to education for adult women in the NLSY97 sample from 2010 to 2021. I explained why and how selection into education and selection into employment bias the estimated return, and the popular techniques used to correct these biases. As it turns out, the biases are in opposite directions, and so a combined model which corrects for both of them simultaneously is approximately the same as simply averaging the results from each model separately. Averaging the estimates from my 6 models reported below yields a return to education of 10%, which is approximately the same as my main CMP model.

Table 8: Summary of Estimated Wage Effects

Model	Coefficient	SE
OLS 1	0.084***	(0.003)
OLS 2	0.081***	(0.003)
IV 1	0.131***	(0.008)
IV 2	0.118***	(0.007)
Heckit	0.071***	(0.003)
IV+Heckit	0.097***	(0.006)

Standard errors clustered by participant. *** p<0.01, ** p<0.05, * p<0.1.

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